Computational social science

Dynamic models & agent-based simulations

or

"how to build and play with your own artificial societies"

Course structure

Period IV

Week	Lecture	Exer. dl	Ext. dl	Topic
1	~~Feb 27~~	~~Mar 3~~	Mar 15	~~Introduction to CSS~~
2	Mar 6	Mar 10	Mar 22	Artificial societies & agent-based models
3	Mar 13	Mar 17	Mar 29	Data & digital traces
4	Mar 20	Mar 24	Apr 5	Counting things & analysing text
5	Mar 27	Mar 31	Apr 12	Social networks: structure
6	Apr 3	*	-	Introduction to the project

***Project deadline: May 26**
Project peer review: June 2

Period V

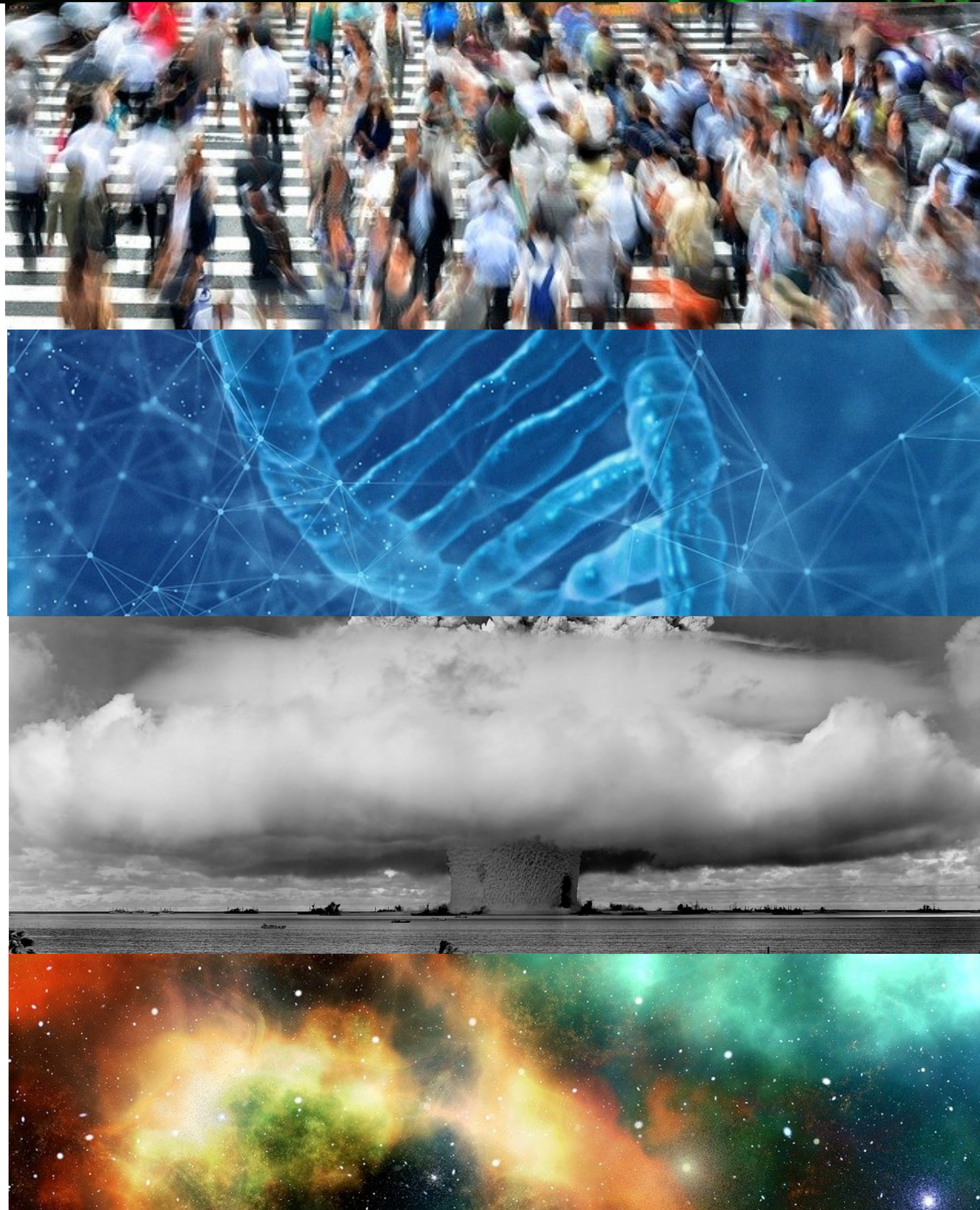
Week	Lecture	Exercise dl	Ext. dl	Topic
7	Apr 24	May 5	May 10	Ethics, privacy, legal
-	-	-	-	WAPPU
8	May 8	May 12**	May 24	Agent-based models & emergence
9	May 15	May 19***	May 31	Social networks: dynamics
10	May 22	May 26***	June 7	Experiments & interventions at scale
11	May 29	-	-	Computing for social good

****Bonus round**
*****Only lecture questions**

Computational Science

Hierarchy of sciences (Comte)

Complex	Social sciences
↑	Biology
	Physics/ chemistry
	Astronomy
Simple	Mathematics



Can we model social systems?

Why to build an agent-based model?

Flexible research questions: how does the behaviour of individual people/companies/countries/etc affect some society-wide phenomena?

Stylistic models

Show how some mechanism(s) lead to emergent phenomena

Microsimulations

Try to model reality as accurately as possible, fitting a model to data.

How does individual behavior lead to societal consequences?

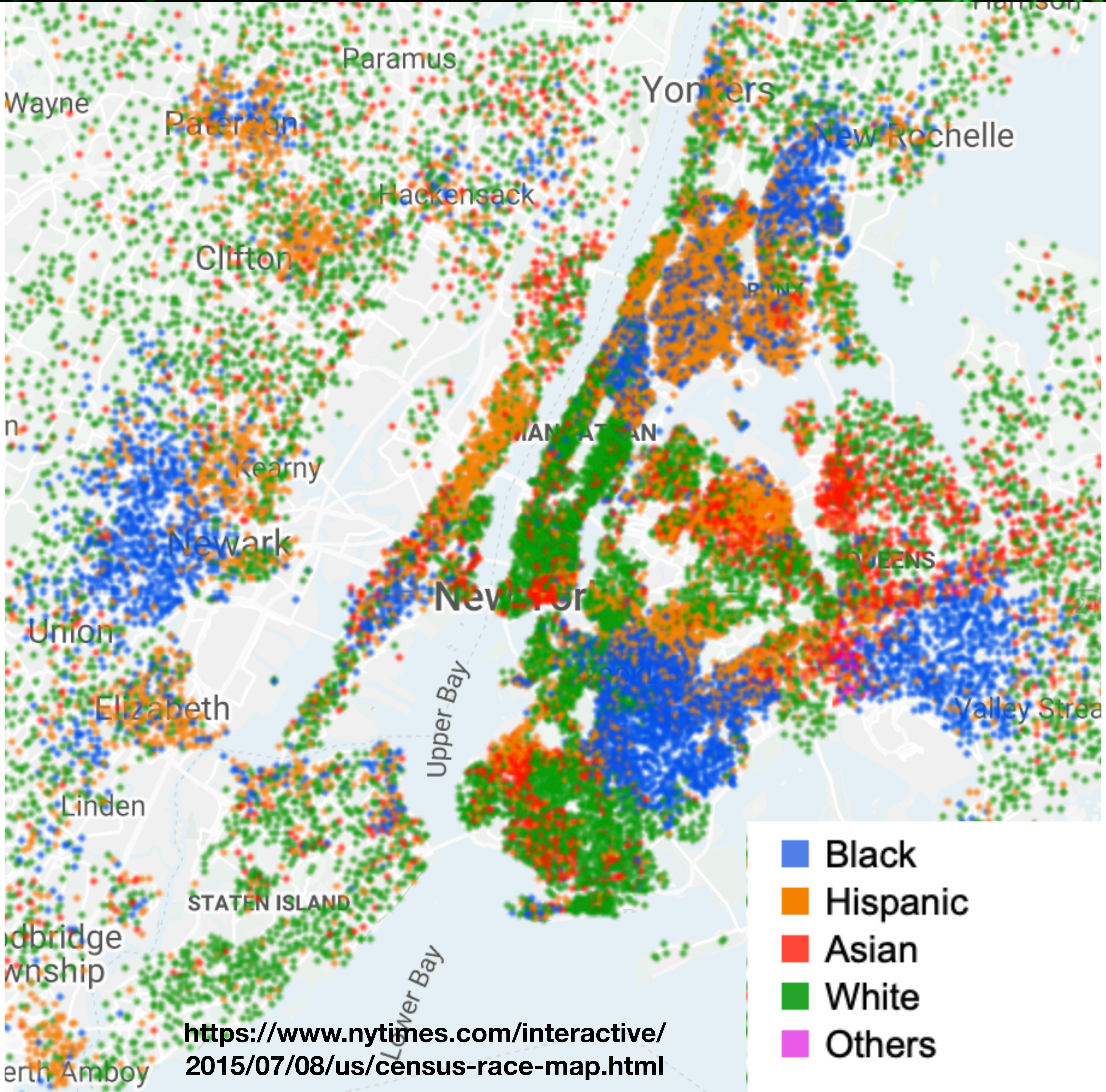
Stylistic models

=

”model of insights,
not for numbers”

Example: Segregation

- Why is there segregation: racially/economically/culturally homogenous neighbourhoods in cities?
- What are the mechanisms producing these?
    - Does it require organisation?
    - Do people only choose to live next to similar people?
    - Could small amount of preference towards similar people be an explanation?



https://www.nytimes.com/interactive/2015/07/08/us/census-race-map.html

Principles of stylistic models

- Computer simulations that model actions of people (bottom-up instead of top-down)
- We cannot or don't need to model every detail of everything: 'model for insights, not numbers'
- Guiding principle 1: Make it as simple as possible
- Guiding principle 2: Anything outside of the core mechanisms is modelled as maximally random

Example: Segregation

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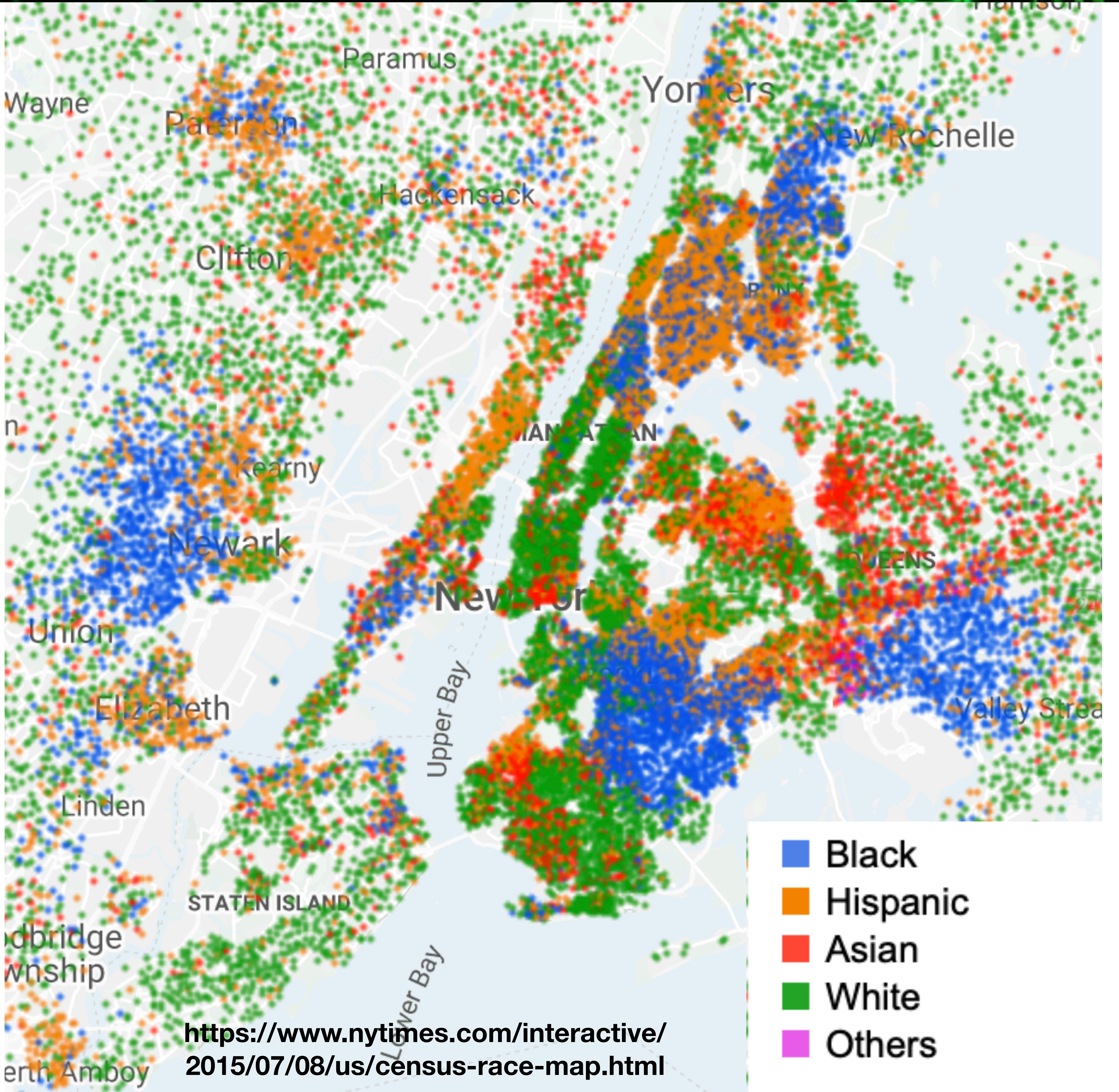

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Example: Segregation

- Why is ther
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Stylistic model

→

Agent-based model

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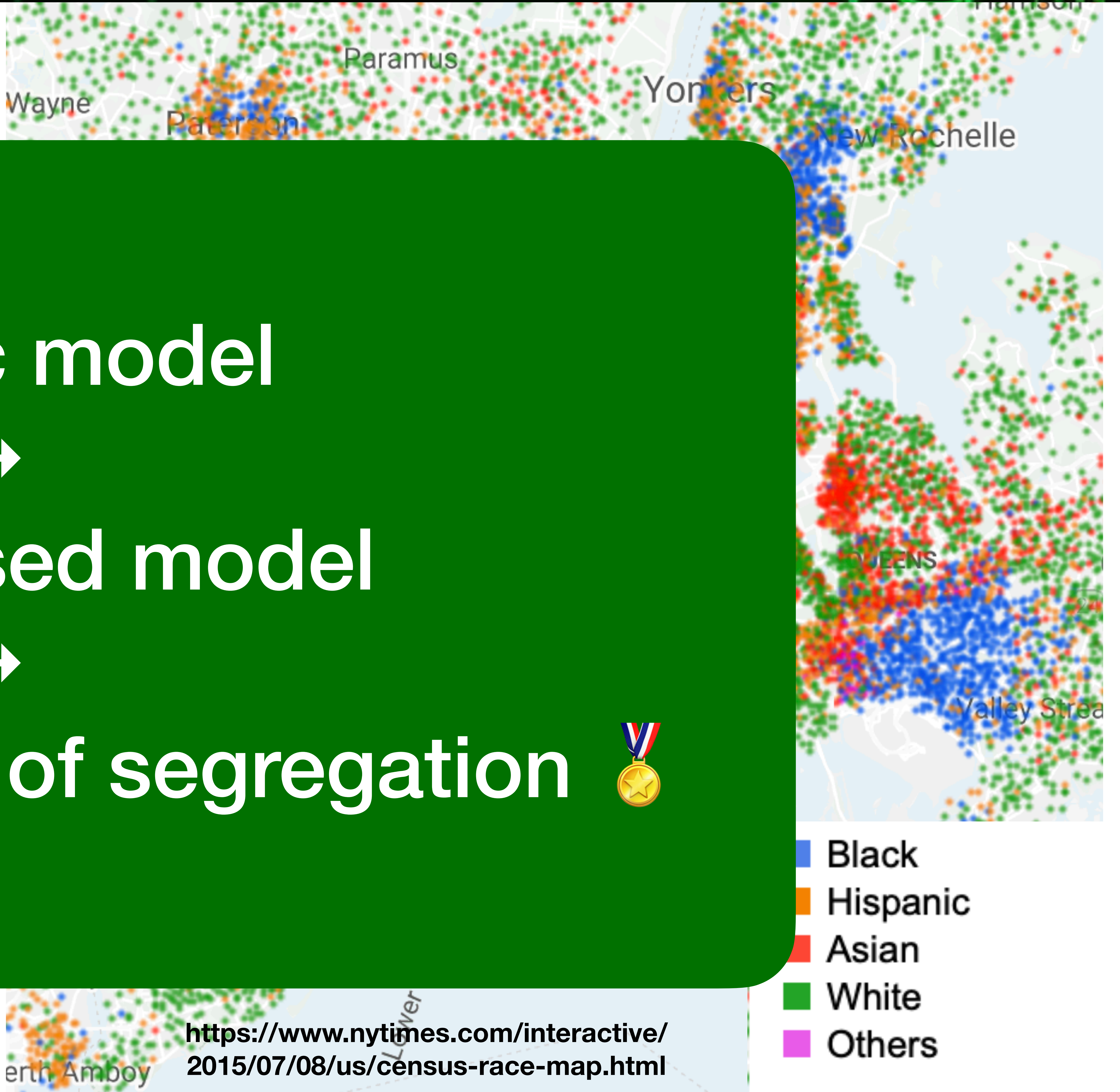
Schelling's model of segregation 🎖️



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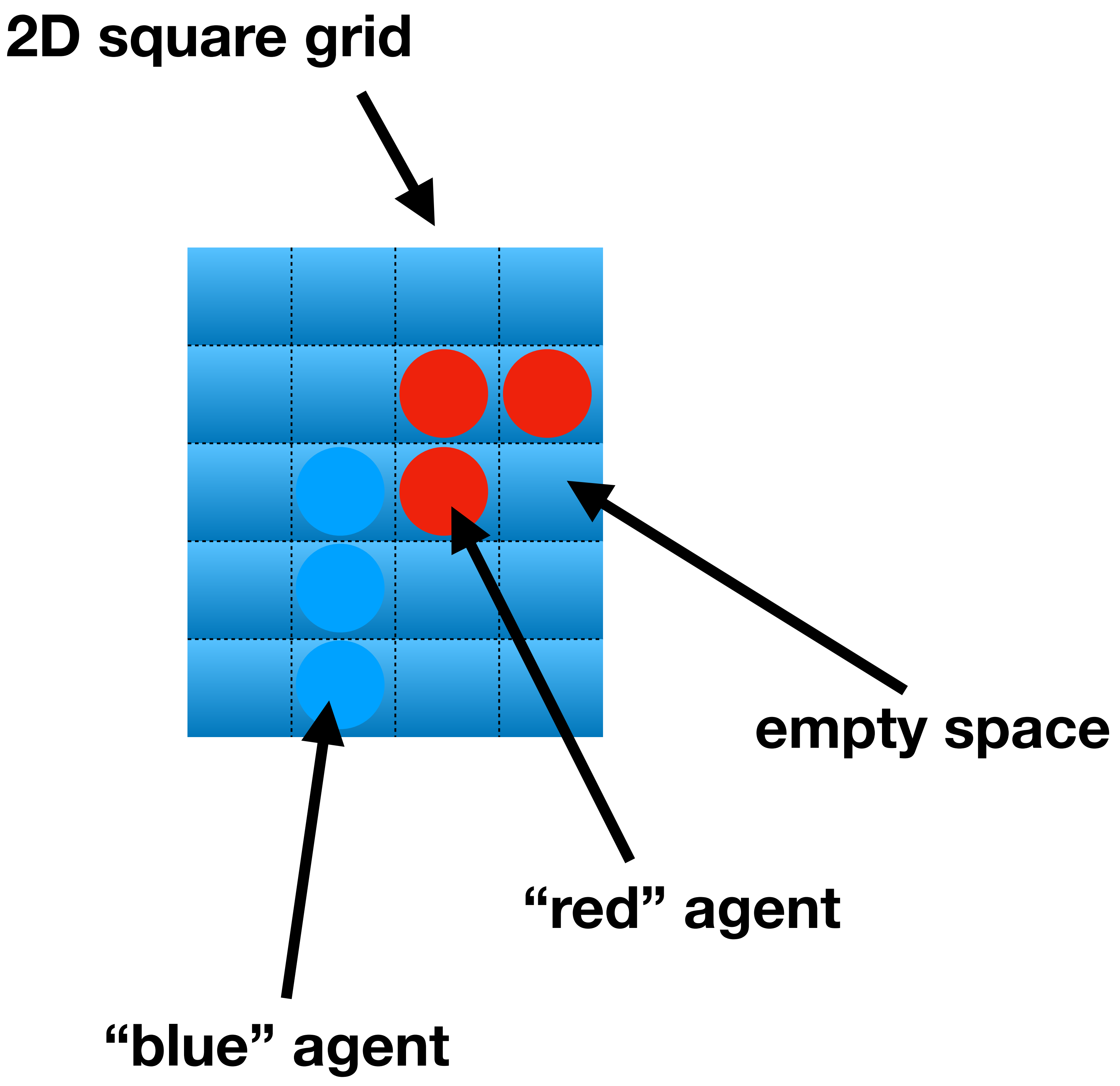
Elements of the Schelling model

Minimal elements needed to model segregation of neighbourhoods?

1. **Environment**: 2D square grid

2. **Agents**: 2 types of households, max one per square



Agents

- Agents represent *the smallest individual units*: Individual people, organisations, countries, …

- Features of agents [1]:

    1. **Autonomy**: Acts independently
    2. **Social ability**: Interacts with other agents
    3. **Reactivity**: Reacts to its environment
    4. **Proactivity**: Takes initiative to fill its goals

[1] Intelligent agents: Theory and practice M Wooldridge, NR Jennings - The knowledge engineering review 10.2 (1995): 115-152.

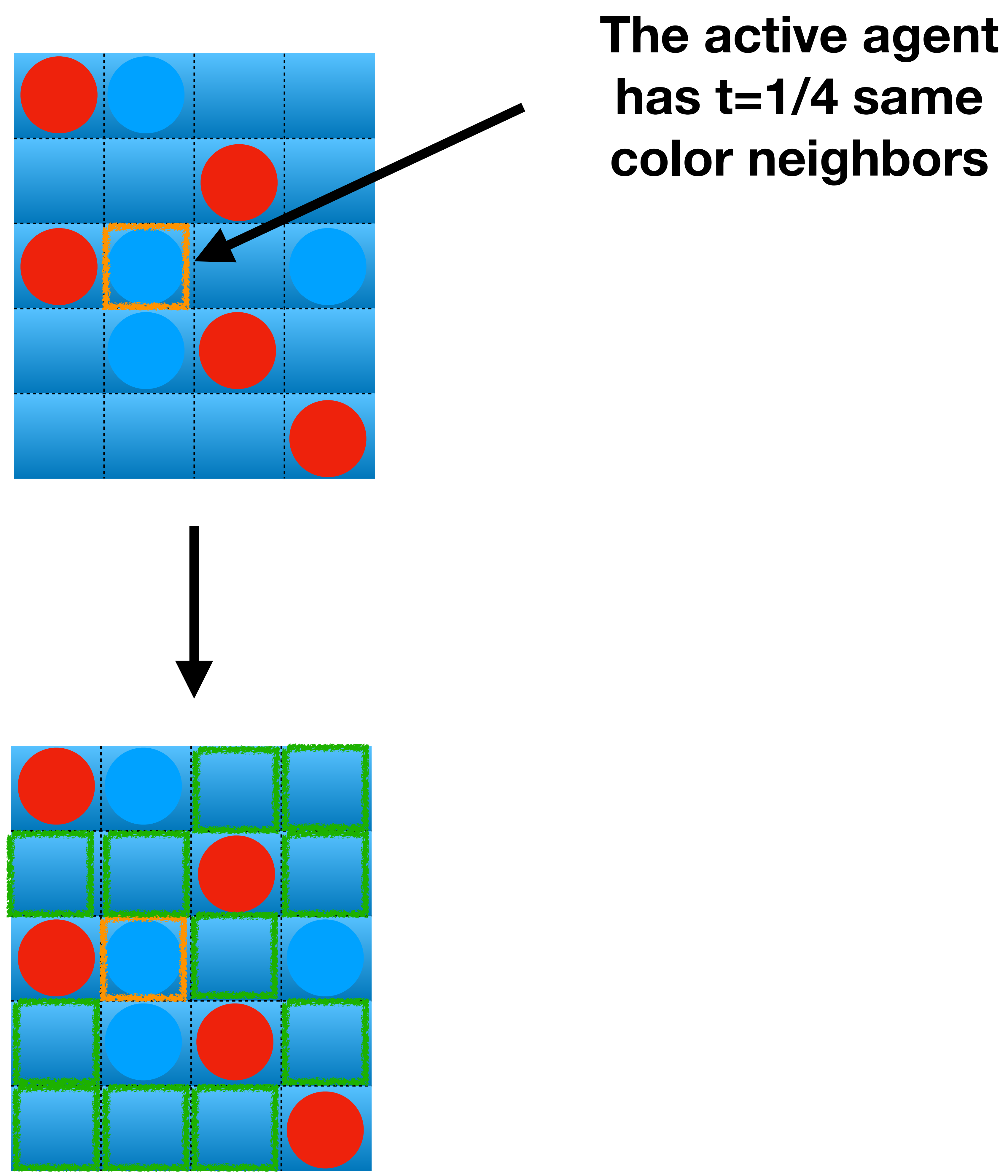
Agents: Schelling model

- *Threshold T*: fraction of same type agents required in a neighbourhood

- Agent inspects its neighbourhood: what is the fraction, t, of same type agents?

- **If t < T**: the agent moves out

- **If t > T**: the agent is satisfied with its position



Agents: Schelling model

- *Threshold T*: how much same type of agents it needs in its neighbourhood

- Agent inspects its neighbourhood: what is the fraction, t, of same type agents?

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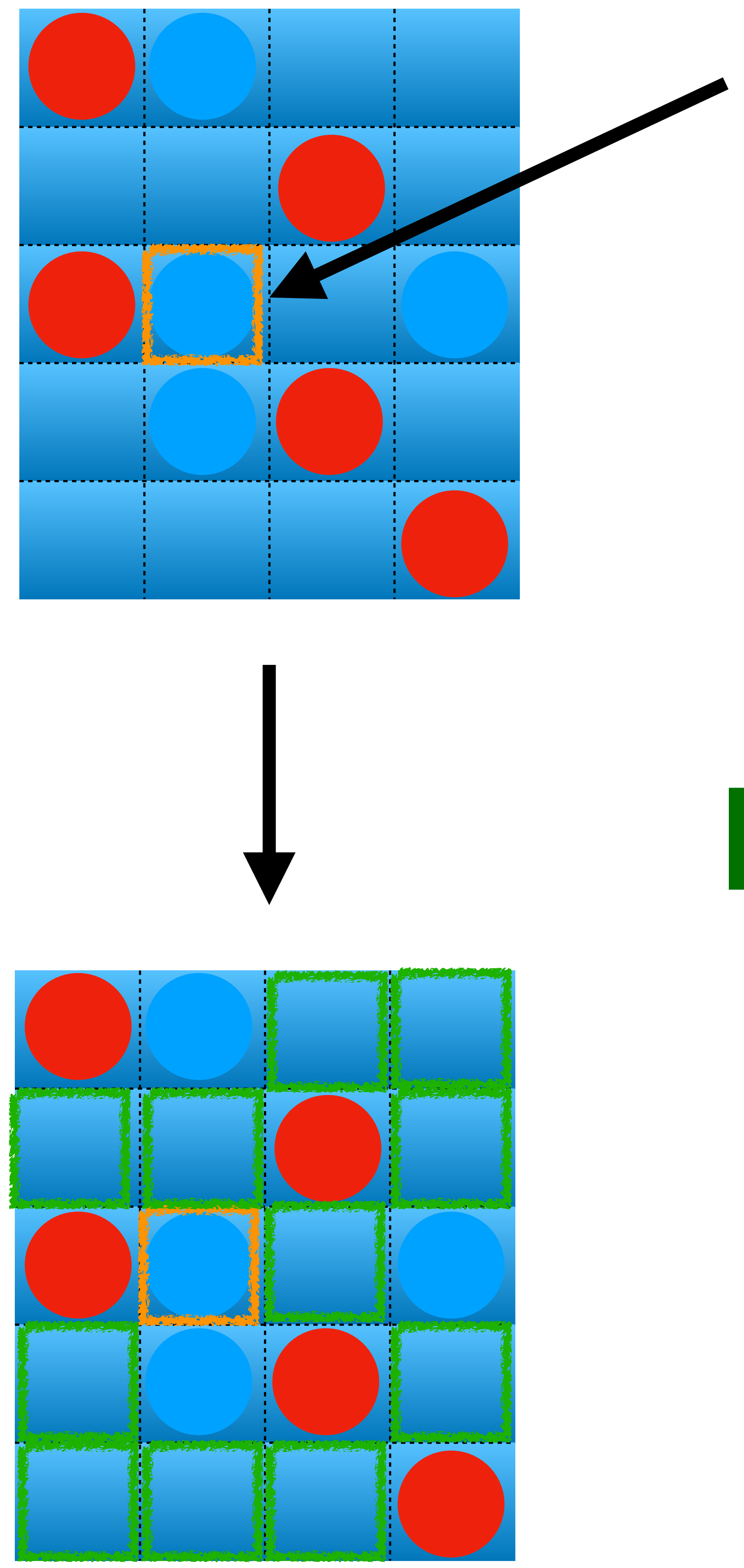
The active agent has t=1/4 same color neighbors



How do we choose where the agent moves?

Missing information = randomness

- We cannot know/model every detail

- **Maximum entropy principle**: In the absence of knowledge, use a probability distribution that is maximally random

→ Choose uniformly random distribution on details that are not modelled

Agents: Schelling model

- *Threshold T*: how much same type of agents it needs in its neighbourhood
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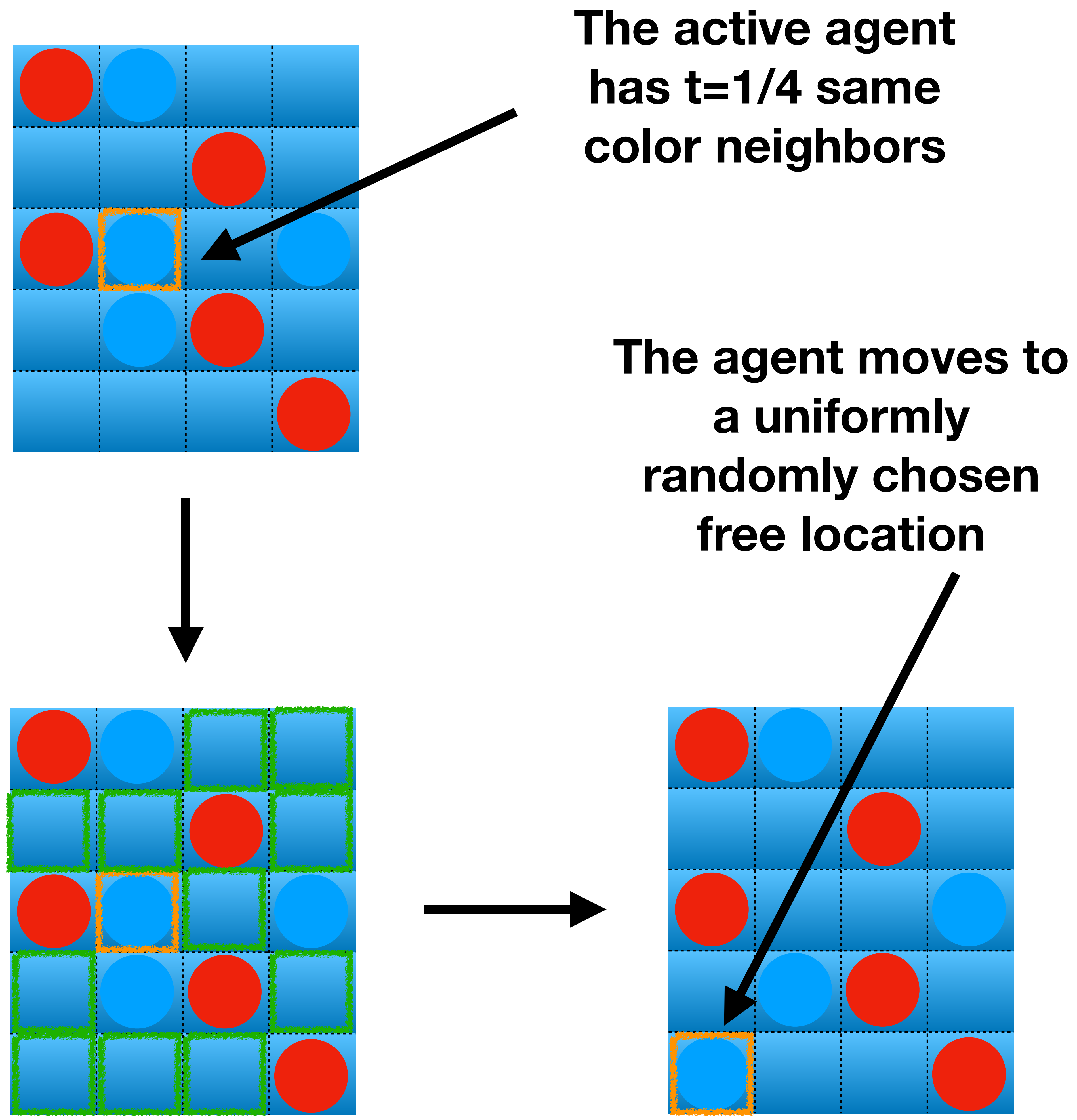


What order are the agents activated?

1. Synchronously (all at once): Might lead to conflicts, e.g., two agents want to move to same space

2. Asynchronously (one at a time):

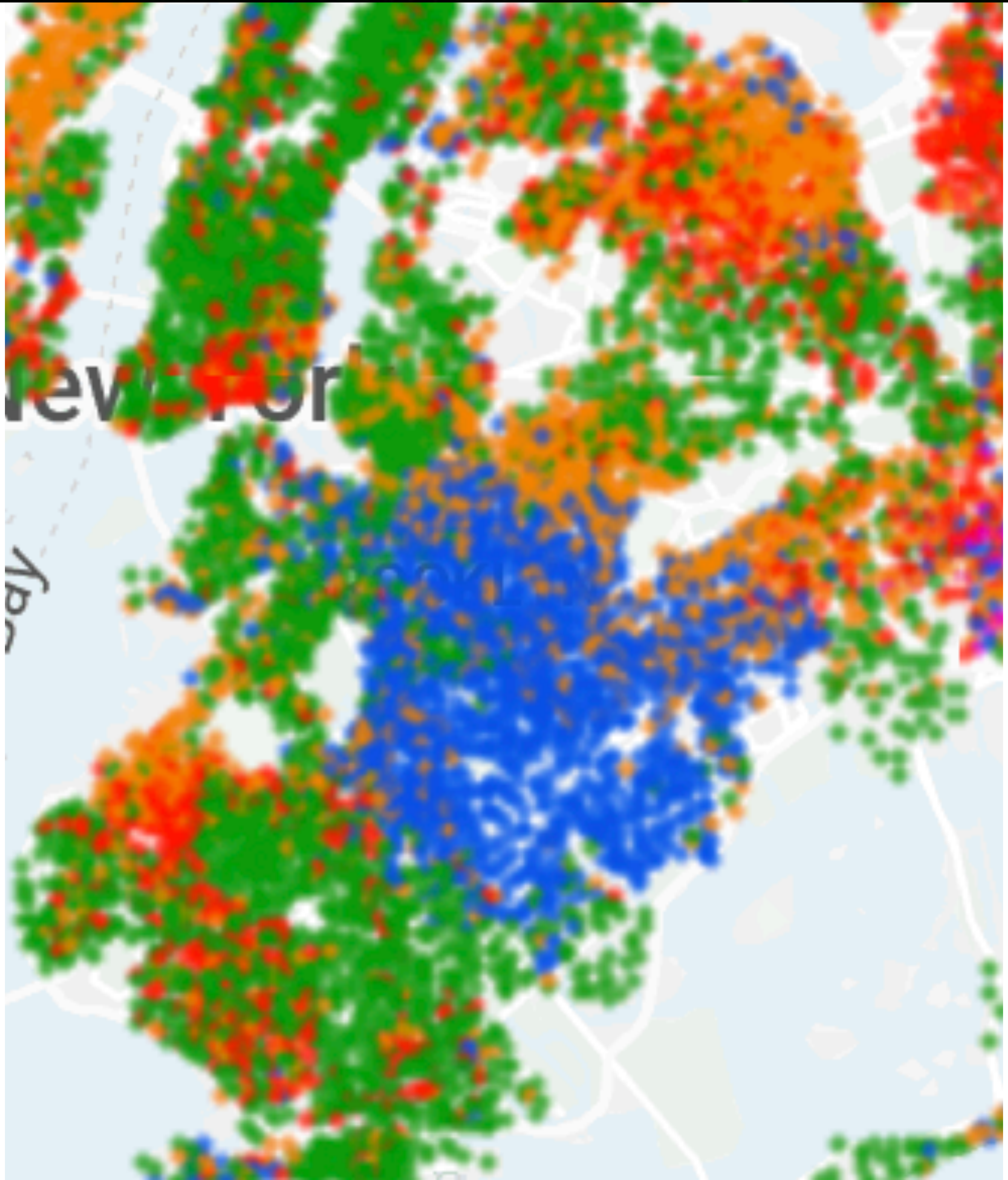
    1. Randomly with replacement.

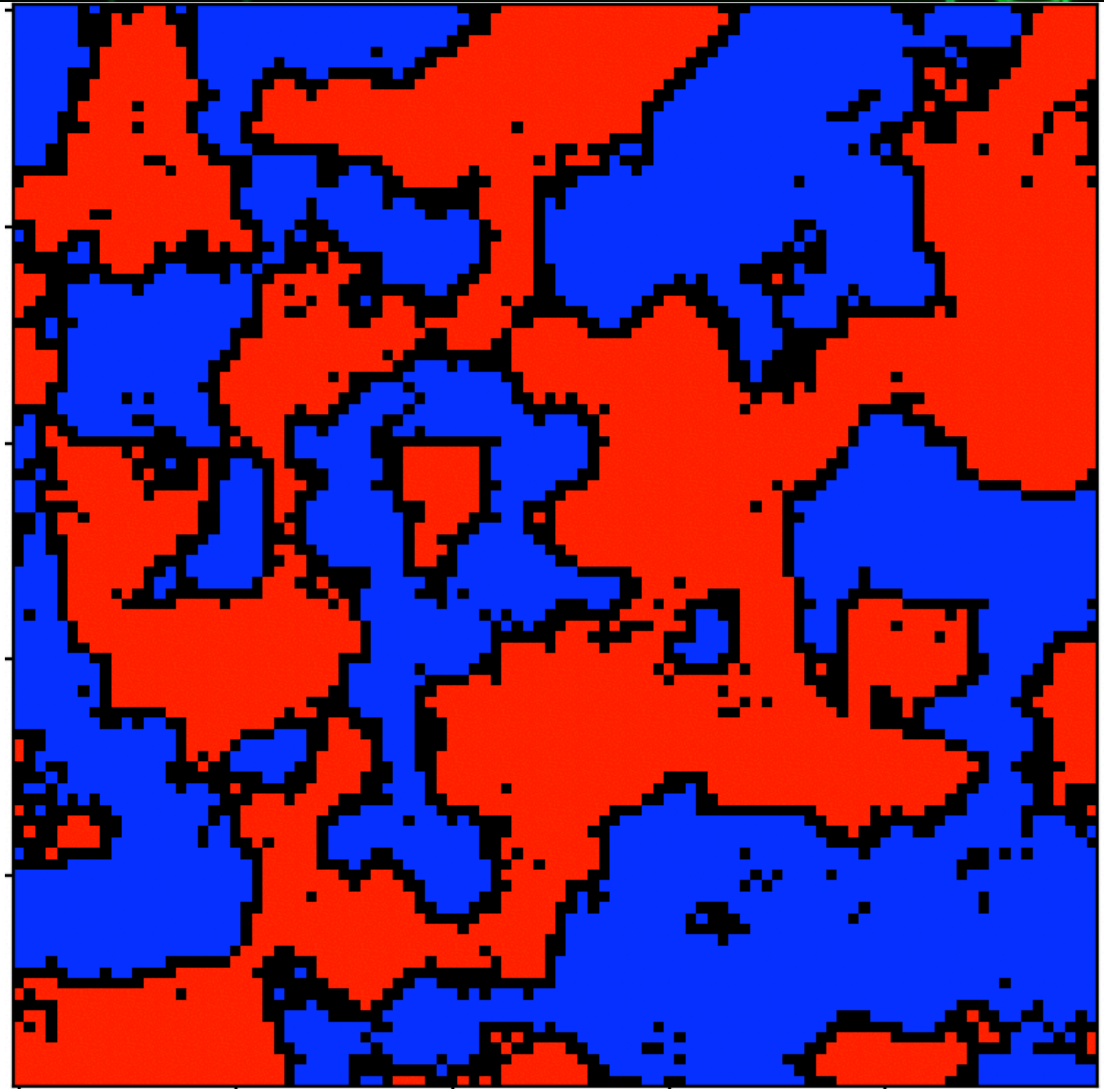
    2. Always in same (random) order. “round robin”

Measuring time

- Number of agent activations as time unit
  - Average number of activations per agent
- Calibration with “real time”?
  - E.g., how many times an average household moves in a year?

Results of the Schelling model





Schelling model, conclusions

1. Segregation can be an emergent phenomenon, no coordination required

2. Only a small preference towards similar neighbors leads to wide segregation

3. Effect is highly non-linear: small changes in preferences can lead to massive overall changes

PROOF LEFT AS AN EXERCISE

How detailed should we go?

What about …

- … multiple types of households
- … geography (bodies of water, hills etc)
- … heterogeneity of households
- …

Summary: elements of an agent-based model

Interactions

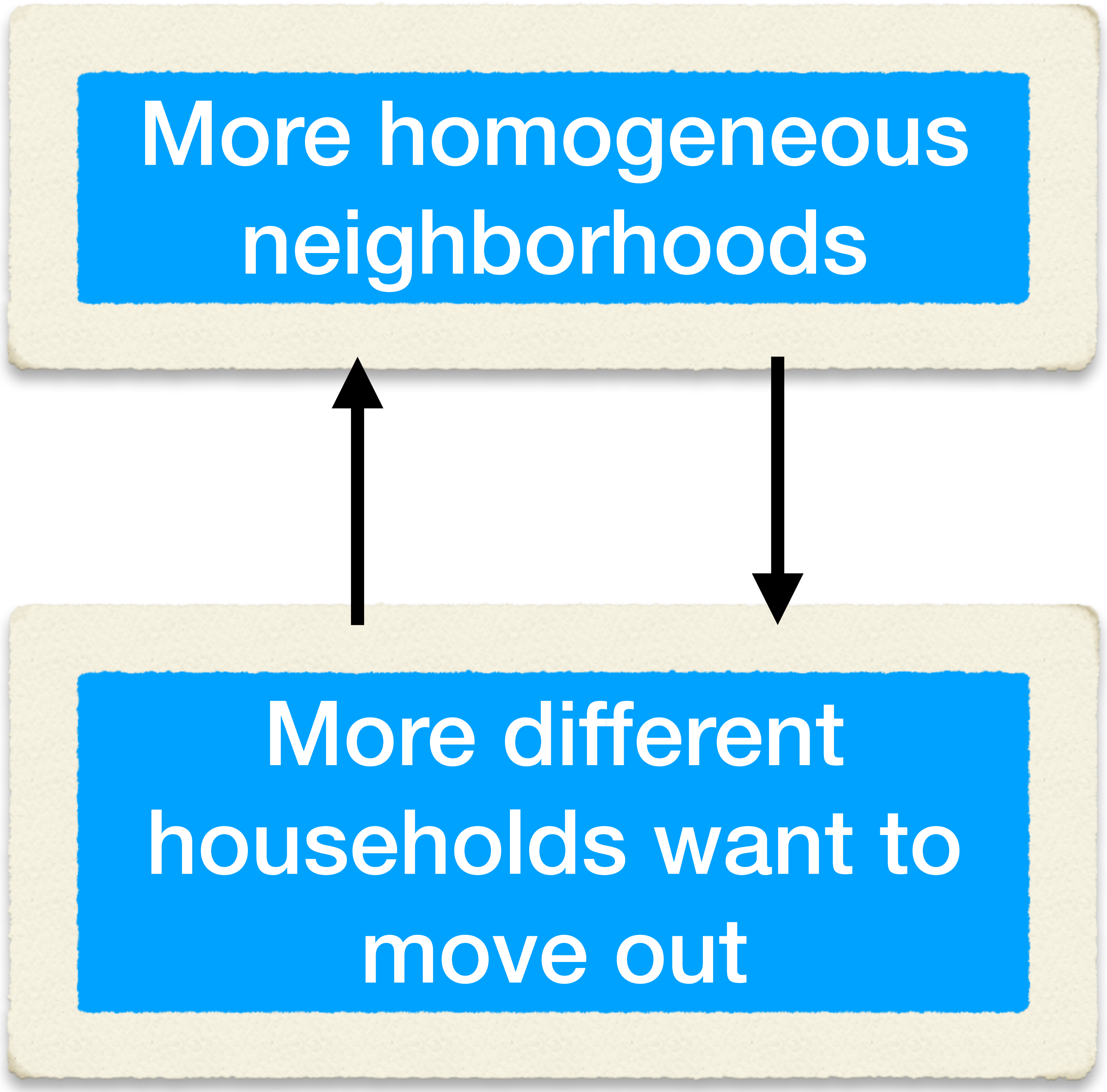
Agents

Environment

When does individual behaviour lead to emergent phenomena?

Feedback loops → emergent phenomena

- Feedback loops lead to emergence
- Typically non-linear as function of model parameters (=phase transitions)



Feedback loops → emergent phenomena

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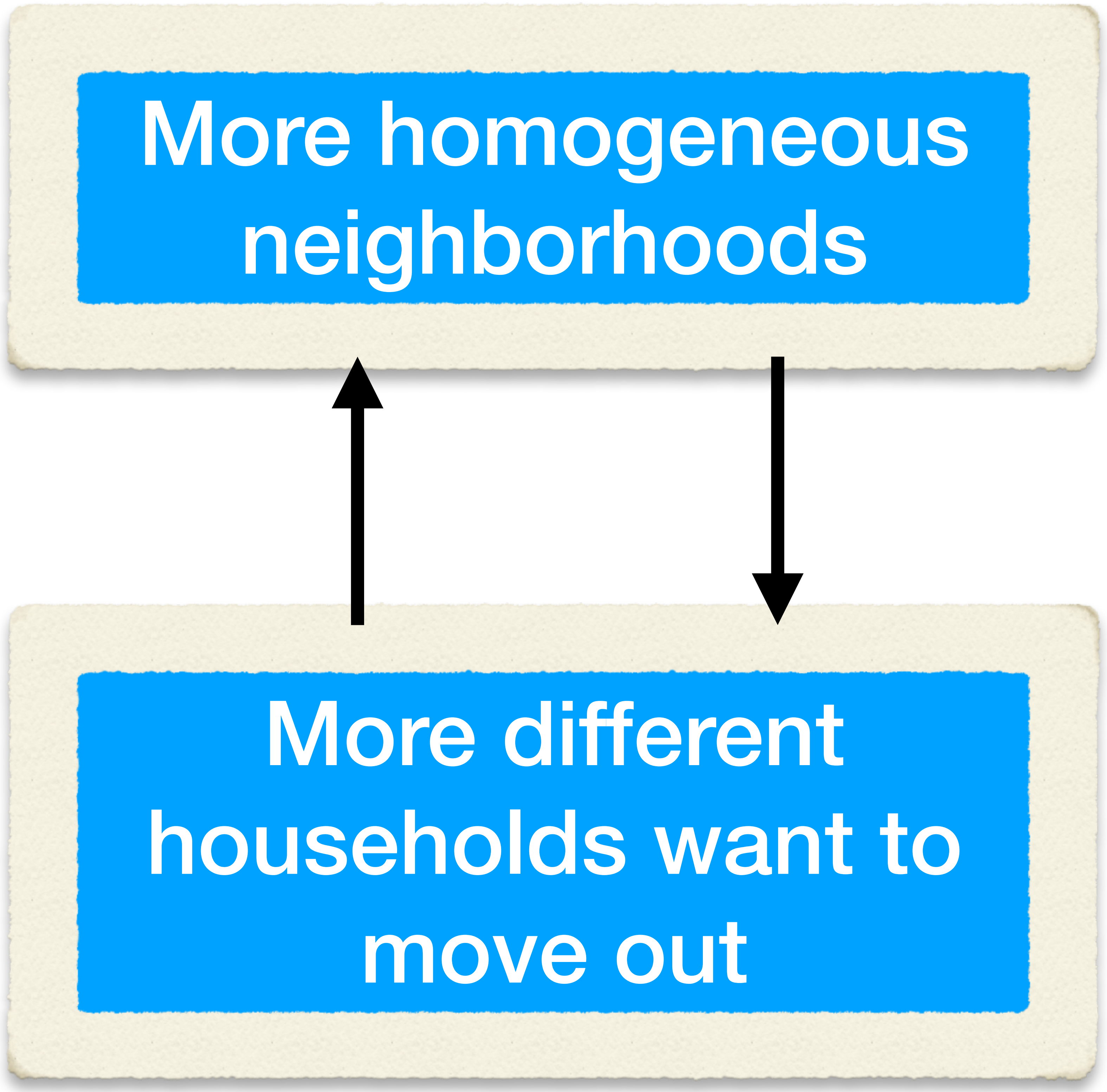


-> More examples & theory in lecture 8

Tools for simulation models

Several software packages exists for simulations

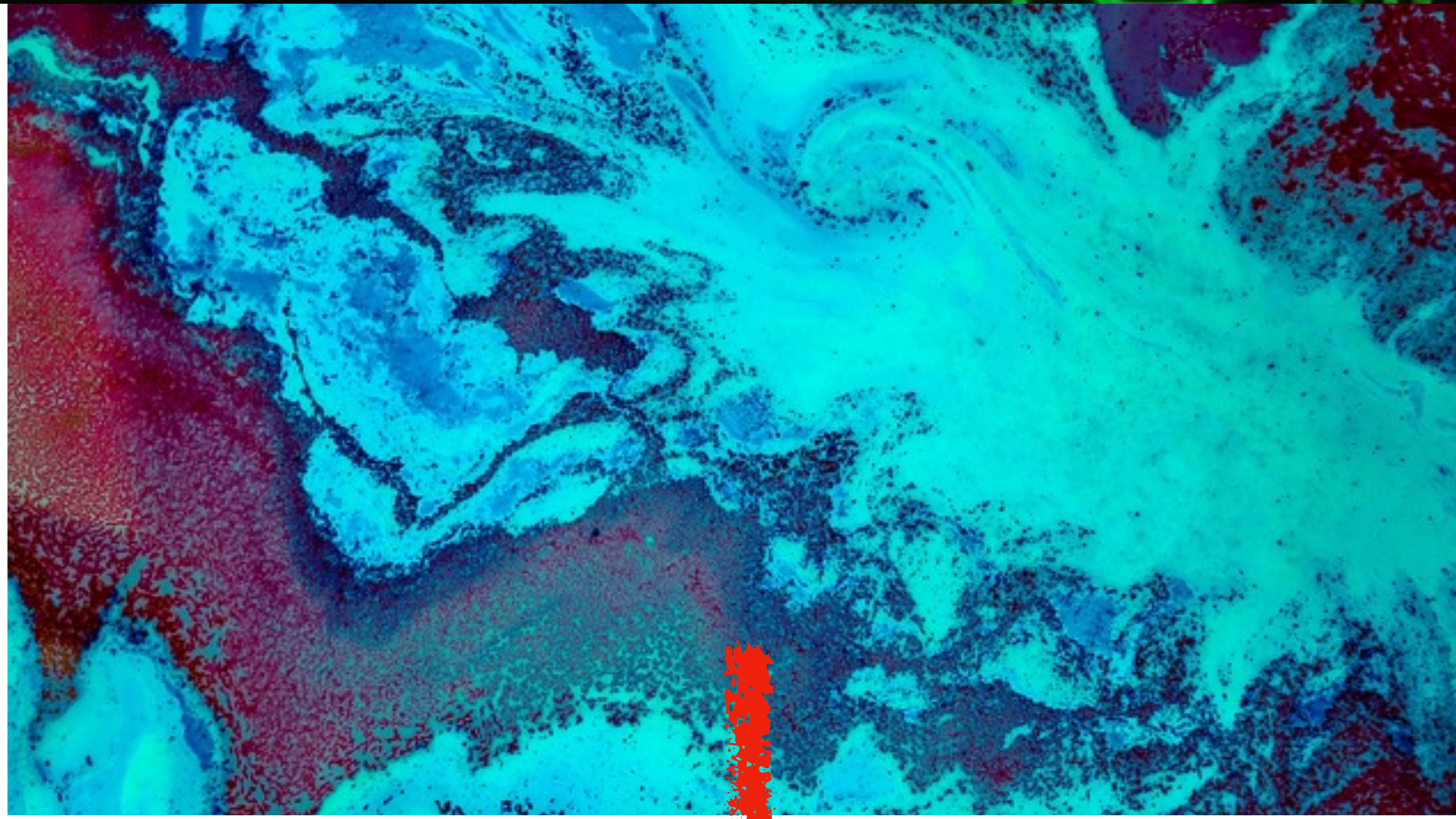
- Easy to get started
- Fast prototyping
- Good performance
- Large libraries of existing models

Example:

NetLogo

https://ccl.northwestern.edu/netlogo/

Microsimulation = model + data



- Model + initialisation with real-world data
- Goal: predict the future, in numbers
- “Weather forecast for a social phenomena”

Microsimulations, pipeline

1. Construct model: agents, interactions, environment

2. Fit the parameters to data (initial conditions + agent interactions)

3. Validate model: compare to data not used for fitting

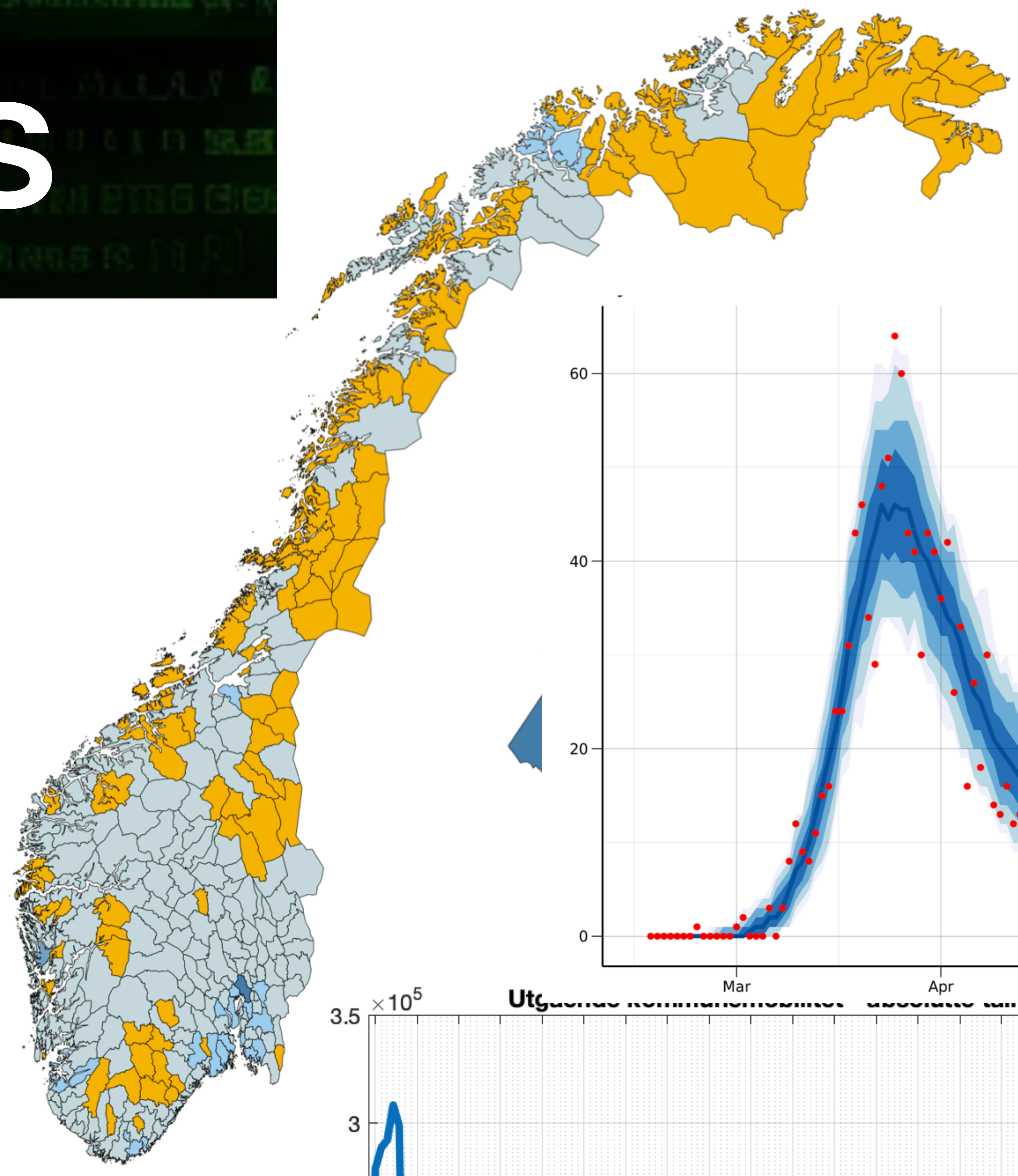
4. Predict future and/or try out counter-factual scenarios

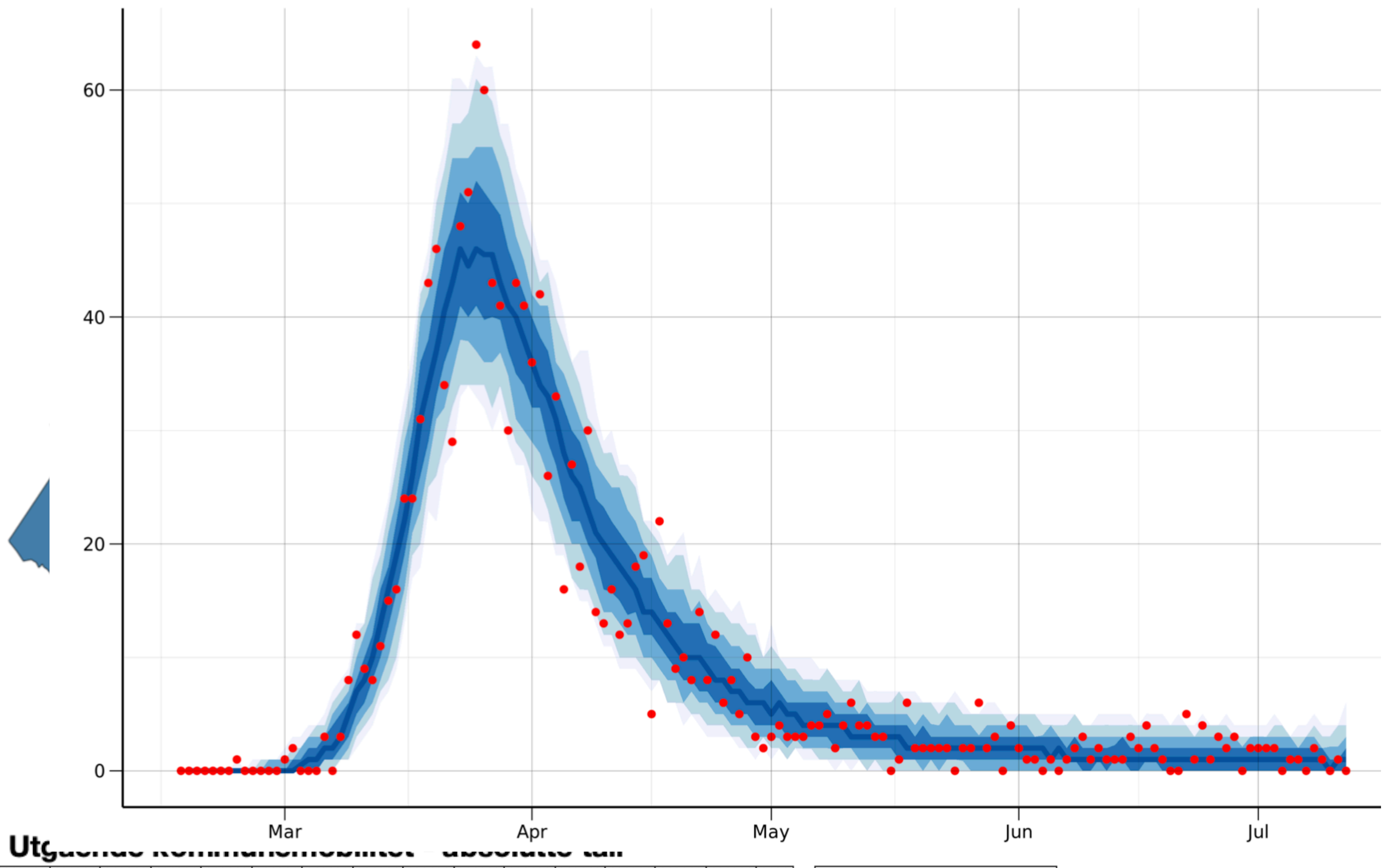
Economic models

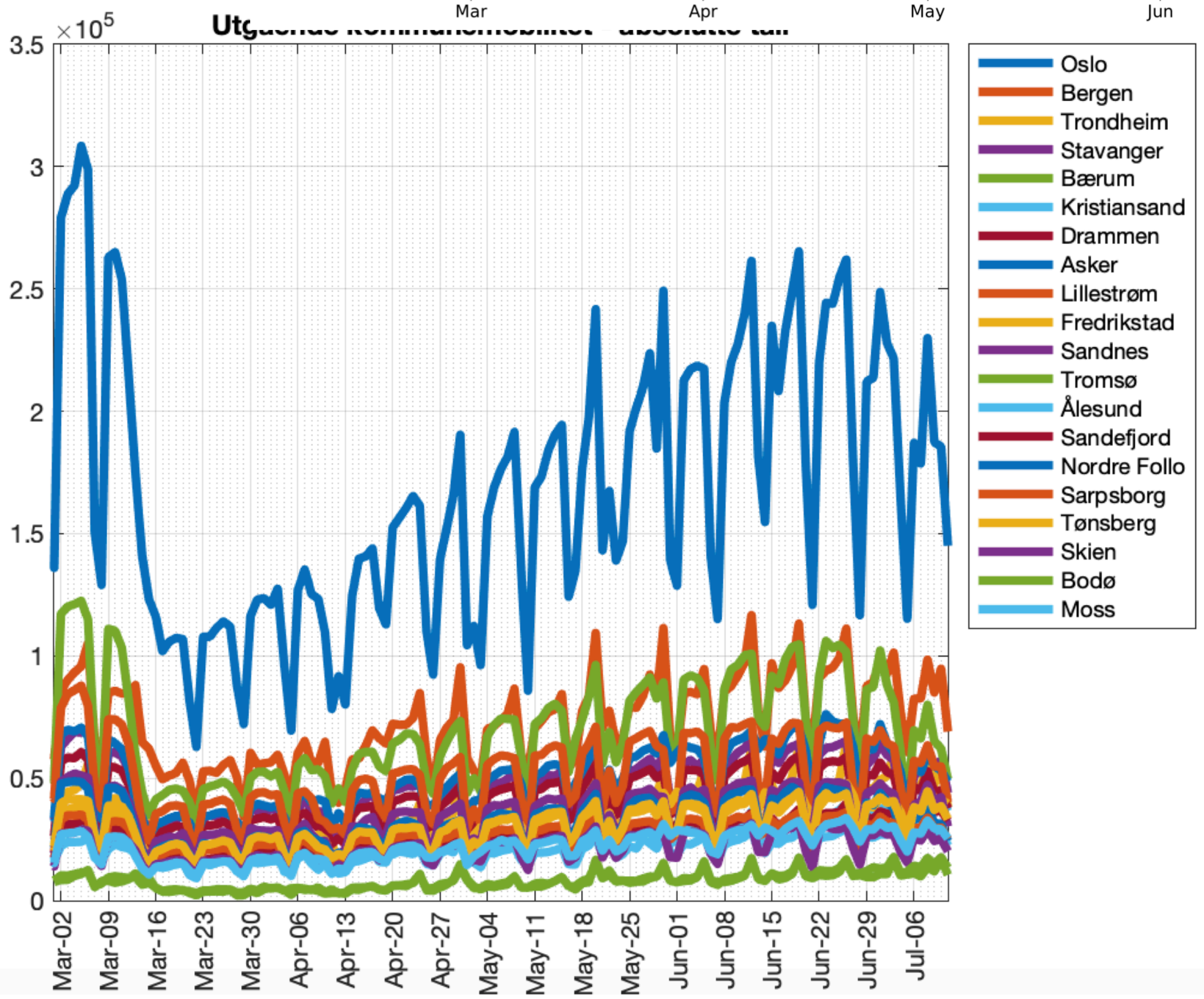
- **Traditionally based on simplistic assumptions**: rationality of agents, equilibrium, perfect information, …
- **Agent-based macroeconomics**: bounded rationality, non-equilibrium, partial information and complex environments, heterogenous agents, …

http://www2.econ.iastate.edu/tesfatsi/amulmark.htm

Epidemic models







NIPH
Norwegian Institute of Public Health

- Traditional epidemic models very simplistic
- Human behavior critical: contacts, mobility, preventive measures, etc
- Observed epidemic situation affects the behavior
- ABMs were used in COVID-19 (see example)

https://www.fhi.no/en/id/infectious-diseases/coronavirus/coronavirus-modelling-at-the-niph-fhi/

Microsimulations, summary

- Model + data → predict the future, in numbers
- Makes it possible to model realistic mechanisms, heterogeneities, …
- Choosing model, finding data, and validation can be difficult

Agent-based models, summary

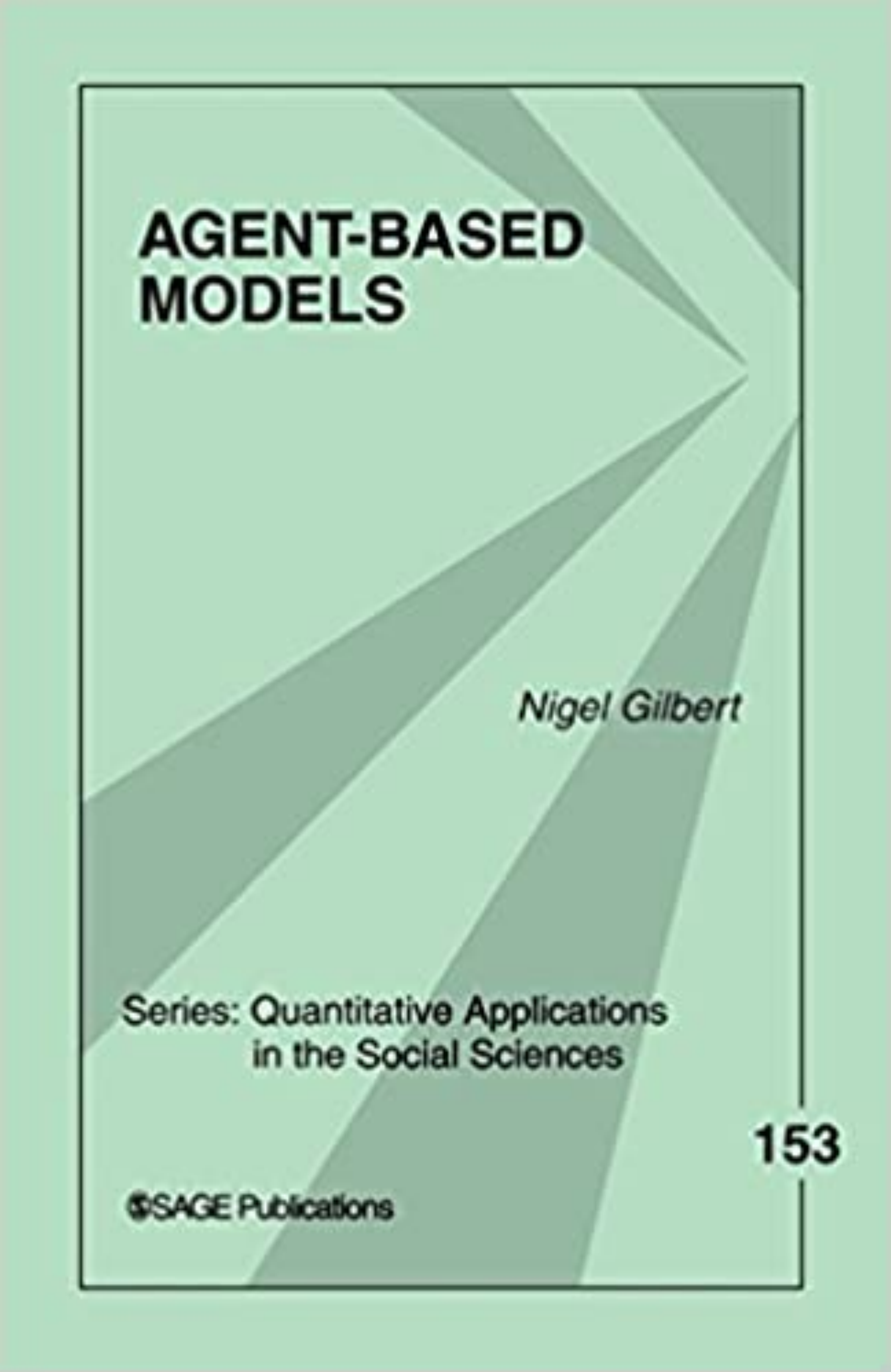
Pros

- Turning qualitative ideas quantitative
- Pathway from microscopic mechanisms to macroscopic phenomena
- Flexible, you can do anything
- Cheap and easy

Cons

- Models are always going to be too simple
- Complex models:
  - Microsimulations: need more data
  - Stylistic: large parameter spaces
- Microsimulations need data (expensive & sensitive)

Further reading



frontiers in Physics

REVIEW
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Mechanistic models in computational social science

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Quantitative social science is not only about regression analysis or, in general, data inference. Computer simulations of social mechanisms have an over 60 years long history. They have been used for many different purposes—to test scenarios, to test the consistency of descriptive theories (proof-of-concept models), to explore emergent phenomena, for forecasting, etc… In this essay, we sketch these historical developments, the role of mechanistic models in the social sciences and the influences from the natural and formal sciences. We argue that mechanistic computational models form a natural common ground for social and natural sciences, and look forward to possible future information flow across the social-natural divide.

arXiv:0710.3256v2 [physics.soc-ph] 11 May 2009

Statistical physics of social dynamics

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Statistical physics has proven to be a very fruitful framework to describe phenomena outside the realm of traditional physics. The last years have witnessed the attempt by physicists to study collective phenomena emerging from the interactions of individuals as elementary units in social structures. Here we review the state of the art by focusing on a wide list of topics ranging from opinion, cultural and language dynamics to crowd behavior, hierarchy formation, human dynamics, social spreading. We highlight the connections between these problems and other, more traditional, topics of statistical physics. We also emphasize the comparison of model results with empirical data from social systems.

Contents

Questions?